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Decoding of Movement Characteristics for Brain Computer Interfaces application

Ying Gu, 2009

Ph.D. Dissertation



SMI CENTER FOR SENSORY-MOTOR INTERACTION

Department of Health Science and Technology



AALBORG UNIVERSITET, Denmark

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Preface

The Ph.D. thesis describes the work carried out at the Center for Sensory-Motor Interaction (SMI), Aalborg University, Denmark and at the Institute of Medical Psychology and Behavioral Neurobiology, Eberhard-Karls-University, Tübingen, Germany, in the period from 2006 to 2009.

Acknowledgements for invaluable helps in this project come from the depth of my heart.

I would like to thank my extraordinary supervisor Prof. Dr. Dario Farina for his expertise, enthusiasm and attention dedicated to this project. Associate Prof. Dr. Kim Dremstrup, the Head of the Department of Health Science and Technology, deserves many thanks for first introducing to me this fascinating topic and guiding me to this path during my Master study. I also would like to express my deepest gratitude to Prof. Dr. Niels Birbaumer, Eberhard-Karls-University, Tübingen, for his passion and support on the clinical study reported in this thesis.

Thanks to Femke Nijboer, Jeremy Hill, Ander Ramos Murguialday, and Sebastian Halder for sharing their knowledge and experience when I worked in Tübingen.

I would like to thank the technical and administrative staff at SMI for efficient support and help throughout the project and the volunteers who participated in the experiments for their patience. My colleagues and friends are also appreciated for their help and friendship.

I appreciate my parents for their unconditional love, support and trust on me.

Thanks to my husband for many encouragements.

Ying Gu

Aalborg, 2009

List of articles

The Ph.D. thesis is based on three articles:

- I Ying Gu, Omar Feix do Nascimento, Marie-Françoise Lucas, Dario Farina. Identification of task parameters from movement-related cortical potentials. *Medical & Biological Engineering & Computing* 2009; 47:1257-1264. (DOI: 10.1007/s11517-009-0523-3)
- II Ying Gu, Kim Dremstrup, Dario Farina. Single-trial discrimination of type and speed of wrist movements from EEG recordings. *Clinical Neurophysiology* 2009; 120:1596-1600. (DOI: 10.1016/j.clinph.2009.05.006)
- III Ying Gu, Dario Farina, Ander Ramos Murguialday, Kim Dremstrup, Pedro Montoya, Niels Birbaumer. Offline identification of imagined speed of wrist movements in paralyzed ALS patients from single-trial EEG. *Frontiers in Neuroprosthetics* 2009; 1:3 (DOI:10.3389/neuro.20.003.2009).

Abstract

The development of an effective communication interface connecting the human brain to an external device, i.e., the brain-computer interface (BCI), has gained increased interests over the past decades. A BCI is usually based on decoding EEG (electroencephalograms) traces and associating commands to them. It aims at providing a new communication channel for patients with severe disabilities bypassing the normal output pathways. In addition, such interface constitutes a powerful tool in neuroscience for a better understanding of the brain. This Ph.D. project has proposed a new BCI paradigm based on distinguishing movement related parameters by motor imagination, which could improve the convenience of use of BCI and increase the degree of freedom of BCI. Besides, it has showed the associations between brain electrical activities and movement related parameters.

The thesis is based on three studies. Studies I and II were conducted on healthy volunteers and focused on the development of the methodology. Study I was based on imagining isometric plantar flexion (lower limb) in four conditions involving two movement parameters: Rate of Torque Development (RTD) and Target Torque (TT). The study aimed at investigating the accuracy in discriminating combinations of these two parameters. The result showed that RTDs could be better distinguished than TTs from single-trial EEG recordings. Study II was based on imagining dynamic movements involving two speeds (fast and slow) and two movement types (extension and rotation) of the wrist. The results showed that the variable “speed” could be better classified than the movement type. The average misclassification rate for healthy volunteers between two tasks was around 20%. These results were promising for the application in patients. Study III was performed on patients who suffer from amyotrophic lateral sclerosis (ALS). The methodology developed and tested on healthy volunteers in the Studies I and II was applied in ALS patients. The ALS patients were asked to imagine wrist extension at two speeds. The instruction on imagery tasks and experimental procedure lasted approximately 30 minutes, which is a substantially shorter time compared with the training time needed by other BCI paradigms. The average misclassification rate obtained in ALS patients was 30%.

In conclusion, the Ph.D. project has indicated that movement-related parameters could serve as an alternative or supplementary input signal for BCI.

Dansk resumé

Der har gennem de seneste årtier været en stigende interesse for udviklingen af et effektivt kommunikationsinterface til at forbinde den menneskelige hjerne til et eksternt apparat, et såkaldt hjerne-computer interface (BCI). Et BCI er normalt baseret på dekodning af EEG (elektroencefalogram) samt tilknytning af kommandoer hertil. Målet er at skabe en ny kommunikationsmetode for patienter med alvorlige handicaps, metoder som omgår personens manglende kommunikationsforbindelser. Endvidere vil et sådant interface blive et stærkt værktøj inden for neurovidenskab til at opnå en bedre forståelse af hjernens funktion. Dette Ph.D.-studie har foreslået et nyt BCI-paradigme, som er baseret på adskillelse af bevægelsesrelaterede parametre ved hjælp af motorisk visualisering, hvilket vil kunne forbedre brugen af BCI og forøge frihedsgraden ved eksisterende BCI. Endvidere har studiet påvist sammenhængen mellem hjernens elektriske aktiviteter og bevægelsesrelaterede parametre.

Afhandlingen er baseret på tre studier. Studie I og II blev udført på raske forsøgspersoner og omhandlede udvikling af metodologien. Studie I var baseret på billeddannelse af isometrisk plantarfleksion (membrum inferius) under fire forhold med to bevægelsesparametre: Rate of torque-udvikling (RTD) og target torque (TT). Studiet havde til formål at undersøge præcisionen i kombinationer af disse to parametre. Resultatet viste, en bedre adskillelse af RTD end TT fra single-trace EEG-optagelser. Studie II var baseret på visualisering af dynamiske bevægelser med to hastigheder (hurtig og langsom) og to bevægelsestyper (ekstension og rotation) af håndleddet. Resultatet viste, at den variable "hastighed" bedre kunne klassificeres end bevægelsestypen. Den gennemsnitlige misklassificeringsrate for raske forsøgspersoner var ca. 20%. Disse resultater er lovende for anvendelse hos patienter. Studie III blev udført med patienter, som lider af amyotrofisk lateral sklerose (ALS). Den metodologi, som var blevet udviklet og testet på de raske forsøgspersoner i studie I og II, blev anvendt på ALS-patienter. ALS-patienterne blev bedt om at forstille sig en ekstension af håndleddet med to hastigheder. Vejledningen i visualiseringsopgaverne og den eksperimentelle procedure tog ca. 30 minutter, hvilket er betydeligt kortere end den træningstid, som kræves i forbindelse med andre BCI-paradigmer. Den gennemsnitlige misklassificeringsrate for ALS patienter var 30%.

Endelig har Ph.D.-studiet indikeret, at bevægelsesrelaterede parametre kunne tjene som et alternativt eller supplerende inputsignal for BCI.

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1. Introduction

Millions of people worldwide suffer from severe motor disabilities as result of accidents and neurological diseases. These persons can hardly communicate and have no effective control over limb movement. They depend on extensive care from others and their families' quality of life is greatly impaired (Moss et al., 1996). Conventional assistive technologies, which depend on the user's residual motor ability, are not effective for these patients since severe motor disabilities preclude their use of voluntary muscle control. Patients in these conditions urgently need ways to restore communication and interaction with the environment. Therefore, it is important and necessary to develop more effective alternative methods for people with severe motor disabilities. Brain-computer interface (BCI) technology is promising in this respect. The ultimate goal of BCI is to provide a non-muscular communication and control channel to convey messages and control the external environment for severely disabled individuals (Wolpaw et al., 2002). BCI would increase the target users' independence and improve their access to new technologies and services. In addition to clinical and quality of life issues, BCIs constitute powerful tools for basic research on understanding brain functions.

1.1 Overview of BCI systems

When the normal pathways of motor functions are interrupted, BCI systems can use signals directly recorded from the brain for communication and control. BCI systems allow continuous and real-time interaction between the user and the environment. They provide an additional non-muscular control channel by using neuronal activity of the brain. Neuronal activity is sampled, amplified, processed in real time, and translated into commands to control an application, such as a prosthetic arm or a communication program.

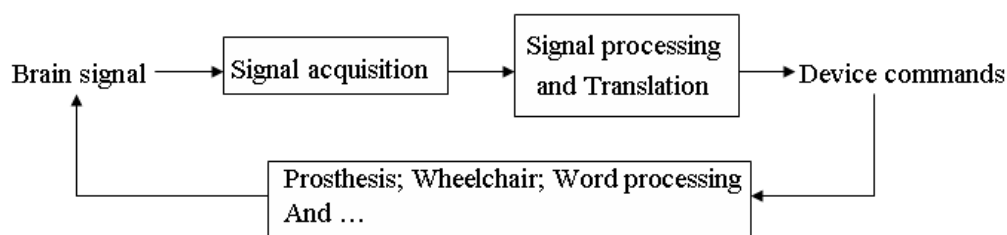


Figure 1. Overview of a BCI system.

Figure 1 above shows a closed loop BCI system. It consists of two adaptive systems: the brain of the users and the machine learning. User's learning involves learning to voluntarily regulate brain activity through an online feedback procedure. After repeatedly training, subjects can learn to manipulate the brain activity of interest, which is to a certain extent under voluntary control. The machine learning algorithm is individually adapted to the user to compensate inter-user variability and relocate the part of training burden from the user to the machine. Machine learning often requires examples from which the underlying statistical structure of the brain signals can be estimated. Therefore, subjects are first required to repeatedly and randomly produce certain brain states during a calibration session. The brain signals are then translated

into an output, which could be a cursor movement on a screen, the position of a prosthetic arm, or the selection of a character. The user receives the feedback on the output, which in turn affects the user's brain activity and influences the subsequent output. Therefore, the effective use of a BCI depends on the mutual adaptation between user learning and machine learning. How to bring these two interacting systems optimally together is one of the most important challenges of BCI research and development (Daly and Wolpaw, 2008).

Brain signals in forms of electrical, magnetic or metabolic changes can be measured and recorded non-invasively or invasively. Invasive recordings either measure the brain electrical activity on the surface of the cortex (electrocorticography, ECoG) or within the cortex (action potentials; local field potentials, LFP). Non-invasive recordings are obtained as electrical activity from the scalp (electroencephalogram, EEG), magnetic field fluctuation (magnetoencephalogram, MEG) or metabolic changes (functional magnetic resonance imaging, fMRI; near infrared spectroscopy, NIRS). Each recording technology has its advantages and limitations with respect to spatial and temporal resolution as well as portability, cost and risks for the user. Generally, MEG and fMRI are expensive and bound to laboratory conditions. Thus, these techniques are suitable for basic research or short-term location of sources of brain activity for early stage BCI screening. In contrast, EEG, invasive recordings, and NIRS have usually lower cost and are portable, thus they may offer practical ways to use BCI systems in daily life. The main advantage of invasive approaches is the good signal quality and signal selectivity. The multidimensional control of neuroprostheses was achieved in non-human primates by means of invasive recordings (Donoghue, 2002). However, invasive methods require surgery for the implantation of the electrodes, which implies an inherent medical risk. Invasive methods have to prove substantially better performance than non-invasive methods in order to become attractive for target users. Currently, the large majority of BCI research and applications in humans are based on EEG signals due to the high temporal resolution, low cost and risk, and portability. This Ph.D. project is based on recording and analysis of EEG signals. Therefore, the following parts will focus on EEG-based BCI technology.

1.2 EEG-based BCI technology

EEG records the electric potential difference between electrodes on the human scalp. The shapes and arrangement of cerebral neurons make it possible to monitor the brain electrical activity by EEG. The pyramidal neurons are arranged perpendicular to the surface of the cortex (illustrated in Fig. 2) and believed to be the main generator of EEG. Both excitatory postsynaptic potential (EPSPs) and inhibitory postsynaptic potential (IPSPs) contribute to the synaptic activity recorded as EEG (Olejniczak, 2006). Further, recordable scalp potential is a result of synchronous activity of a large number of neurons. Brain electrical activities are volume-conducted through the skull and scalp, which results in considerable attenuation of the activity, especially for high frequency components.

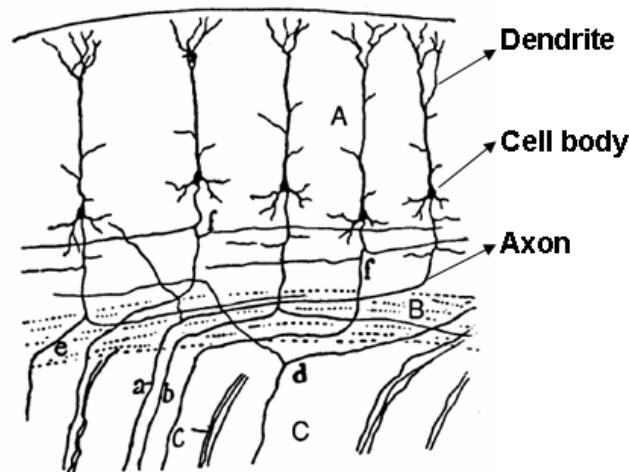


Figure 2. Pyramidal cells in cerebral cortex (adapted from Regan, 1989).

EEG was first recorded by Berger in 1930. The oscillations of EEG depend on the degree of alertness. Several waves oscillating at specific frequency ranges have been consistently observed. α -wave (8-13 Hz) can be observed in awake adults with closed eyes. β -wave (14-30 Hz) will dominate with open eyes and normal alert consciousness. θ -wave (4-7 Hz) is associated with deep relaxation. δ -wave (less than 3 Hz) occurs in deep sleep and it tends to be the highest in amplitude and slowest in frequency. The frequency of brain oscillation is negatively correlated with their amplitudes (Figure 3). EEG is a well established recording technology for investigating cerebral activities and for clinical applications. Robust EEG correlations with brain states, mental calculation, working memory, voluntary movement and selective attention have been revealed. EEG is an important diagnostic tool in the clinics, e.g., as an aid to diagnose epilepsy, to judge the degree of maturity of the brain, to monitor anesthesia and diagnose of brain death (Despopilous and Silbernagl, 1991).

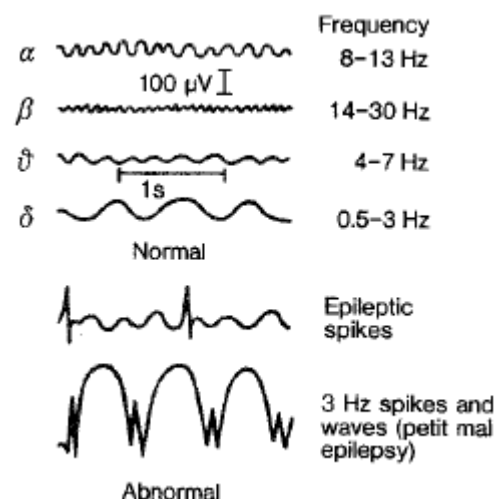


Figure 3. EEG waves (adapted from Despopilous and Silbernagl, 1991).

The most widely used method to describe the location of scalp electrodes for EEG recording is the international federation 10-20 system of electrode placement (Klem et

al., 1999), which stems from an attempt to place particular electrodes over particular brain areas independently of the skull size. As showed in Figure 4, the name of each site consists of a letter, which identifies the lobe, and a number, which identifies the hemisphere location. The letters used are F for Frontal lobe, T for Temporal lobe, C for Central lobe, P for Parietal lobe and O for Occipital lobe. Even numbers refer to the right hemisphere and odd numbers refer to the left hemisphere. Z refers to an electrode placed on the midline. The smaller the number is, the closer the position to the midline. Fp stands for Front polar. Nasion is the point between the forehead and nose. Inion is the bump at the back of the skull. The space between electrode and scalp should be filled with conductive gel, which serves as a medium to ensure lowering the contact impedance at the electrode-scalp interface.

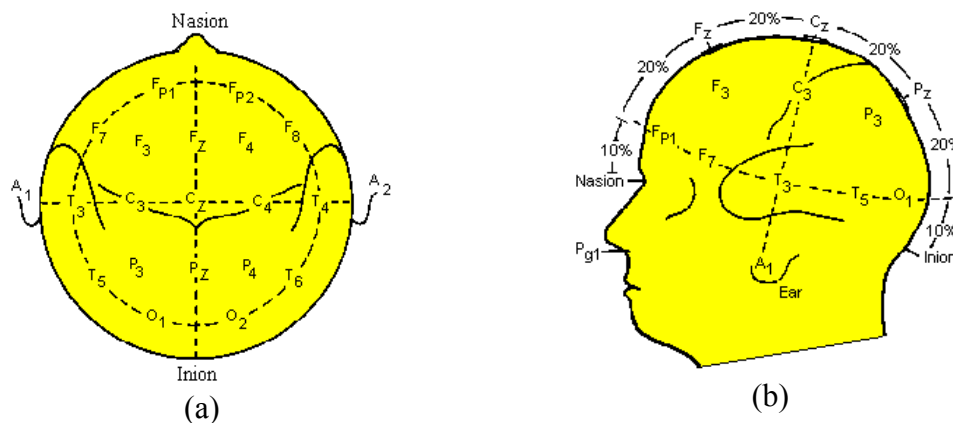


Figure 4. The 10-20 system of electrode placement. (a) top view; (b) left side view. (adapted from <http://faculty.washington.edu/chudler/1020.html>).

BCI technology is based on the ability of individuals to voluntarily and reliably produce changes in EEG signals (Curran and Stokes, 2003). In a large part of BCI research to date, cognitive tasks are used to generate EEG changes which could be distinguished with some success. Results have been published on distinguishing motor imagery (hand closing and opening) from non-motor imagery (mental arithmetic) (Penny et al., 2000). Moreover, alternative approaches, such as discriminating between cognitive tasks (composing a letter, mathematical thoughts, visual counting and geometric figure rotation) have been attempted (Keirn and Aunon, 1990; Anderson and Sijercic, 1996). Most BCI studies using cognitive tasks employed motor imagery (McFarland and Wolpaw, 2005; Pfurtscheller et al., 2006). This PhD project is based on analyzing brain electrical activity from motor imagery. Therefore, the underlying neurophysiology related motor imagery will be introduced in flowing paragraph.

1.3 Underlying neurophysiology

Voluntary movements are goal directed and improve with learning and practice. All the body's voluntary movements are controlled by the brain. The cerebral cortex is the body's ultimate control and information processing center. The cerebral cortex is divided by sulci or grooves into four major lobes: frontal, parietal, occipital and temporal lobes (Figure 5). Each lobe engages in different jobs. The frontal lobe associates with reasoning, planning, parts of speech, movement, emotions and problem solving, the parietal lobe with movement, orientation, recognition and

perception of stimuli, the occipital lobe with visual processing and the temporal lobe with perception and recognition of auditory stimuli, memory and speech. The cerebral cortex consists of two hemispheres. The right hemisphere senses information from the left side of the body and controls movement on the left side. Similarly the left hemisphere is connected to the right side of the body. The two hemispheres are intimately connected between each other by the corpus callosum.

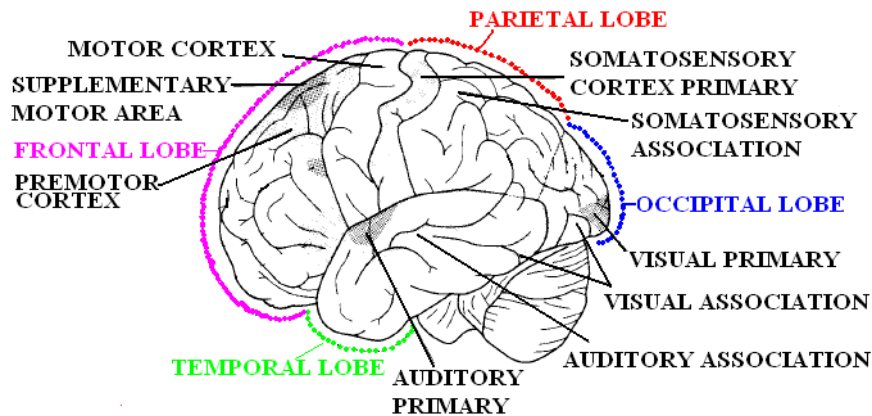


Figure 5. Map of human cerebral cortex showing the major functional areas (adapted from Regan, 1989).

One of the brain areas most involved in controlling voluntary movements is the motor cortex. The motor cortex is subdivided into a primary motor area and several premotor areas. The primary motor cortex is organized somatotopically as shown in Figure 6. The cortical areas assigned to body parts are proportional not to their size, but to the complexity of the movement.

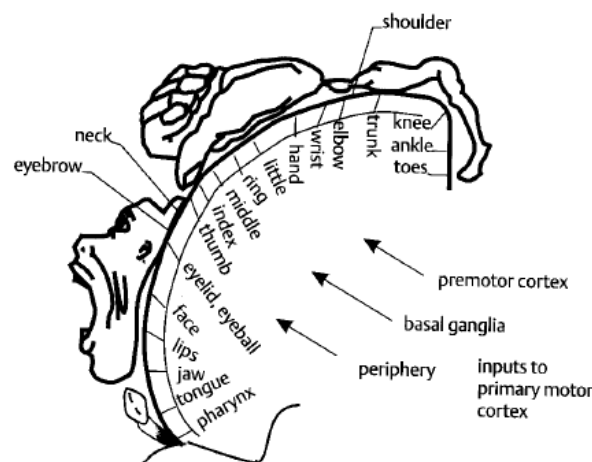


Figure 6. Primary motor cortex, showing relative size of body representation.

Motor imagery obeys the same temporal regularity, programming rules and activates common neuronal substrates as the corresponding real movements (Decety, 1996). The decision to initiate a movement and subsequent execution of movement, with sensory information collected from various lobes of the brain and depending on the characteristics of the movement and its location in the body, give rise to increased electrical activity at the corresponding cortical sites. Specific EEG changes were found during movement planning and movement execution. The following paragraphs describe those changes in EEG components, especially MRCP and SMR. Changes of

MRCs and SMR have been reliably and consistently observed during voluntary movements and imagination of voluntary movements from the same cortical areas. Given that the temporal-spatial pattern of SMR ERD (event related desynchronization) prior to a movement is different from that of MRCP, it suggests that these two are different responses of neuronal structures in the brain (Shibasaki and Hallett, 2006).

MRCP

It has been reported that self-paced movements, movements to a cue and movement imagery evoke MRCP in the motor cortex (Jankelowitz and Colebatch, 2002). MRCP is a slow cortical potential whose surface negativity develops ~2 s before the movement onset; the potential rebounds around movement or imagination onset. It is detected usually by averaging repeated trials in the time domain. The basic assumption is that MRCs are time locked and have more or less fixed time intervals to time marker, while ongoing EEG and background activities behave as random noises. The averaging will enhance the signal (MRCP) to noise ratio. Different terminologies have been proposed for the MRCP components (Table 1).

Table 1. Terminology of MRCP components (adapted from Shibasaki and Hallett, 2006)

	Pre-movement components					Post movement components			
Kornhuber&Deecke (1965)		BP		PMP	MP				RAP
Vaughan et al. (1968)		N1		P1	N2(?)	N2(?)			P2
Shibasaki et al. (1980a) ^a	BP		NS'	P-50	N-10	N+50	P+90	N+160	P+300
Dick er al. (1991)	NS1		NS2						
Lang et al. (1991)	BP1		BP2						
Tarkka & Hallett (1911)	BP		NS'	PMP	isMP ppMP	fpMP			
Kristeva et al. (1991) ^b		RF			MF	MEFI	MEFII	MEFIII	PMF
Cui and Deecke (1999)	BP1		BP2		MP		PMPP	MEPI	MEPII

^a Peak of each component, except for BP & NS', was measured from the peak of averaged, rectified EMG.

^b Based on movement-related magnetic fields.

The MRCP consists of a pre-movement potential (the most investigated component, called Bereitschaftspotential, BP) and a post-movement potential. BP was first recorded and reported by Kornhuber and Deecke at the University of Freiburg in Germany in 1964. Given that the initiation of BP precedes movement onset, it is believed that BP reflects the movement preparation. The amplitude of the BP is maximal over the cortical area representing the moving limb. The contralateral maximum was found for finger and hand movements, while ipsilateral for foot movement. This is because the cortex representing area for foot is located deep in the medial fissure, which results in different ways of cortex projecting potential to the scalp from that for finger and hand (Figure 7) (Brunia and van den Bosch, 1984). The magnitude and time course of MRCP are influenced by the characteristics of the movement (complexity of movement, speed, force exerted, precision) and the subject's psychological status (level of intention, motivation, preparatory state).

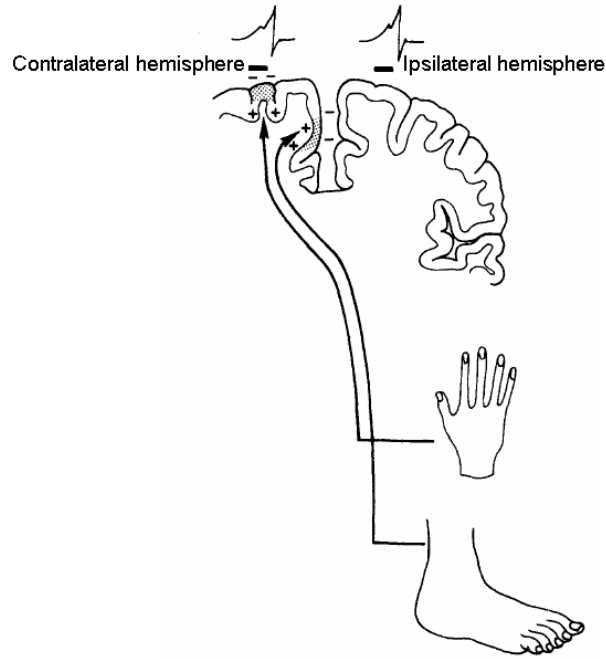


Figure 7. The motor cortex and somatosensory cortex areas representing right hand and right foot located in the left hemisphere. Due to the different directions of dipoles, left hand cortex area produces surface negativity over the left hemisphere, while left foot cortex area produces pronounced surface negativity over the right cortex (adapted from Brunia and van den Bosch, 1984).

ERD/ERS

EEG desynchronization or blocking of alpha band rhythm due to sensory and motor events was first reported by Berger in 1930. Pfurtscheller and Aranibar in 1979 introduced the term ERD and described the techniques for measuring it. The ERD reflects the decrease of oscillatory activity, which represents increased cortical activity. The opposite phenomena, namely increase of oscillatory activity, is called event related synchronization (ERS), which is associated with relaxation and termination of events (Pfurtscheller and Lopes da Silva, 1999). The voluntary movement is observed with power changes of the sensorimotor rhythm. Movement preparation and movement execution are typically accompanied by a power decrease in the mu and beta rhythms in the sensory and motor cortex, particularly contralateral to the movement. ERS of sensorimotor rhythm is observed after termination of movement. ERD/ERS also occur with motor imagery (McFarland et al., 2000; Pfurtscheller et al., 2006). This is in accordance with the concept that the realization of motor imagery occurs via the same brain structures involved in the planning and preparation of actual movements (Decety, 1996). ERD/ERS phenomena are believed to be generated by changes in parameters which control the states of synchrony in neuronal networks (Lopes da Silva, 1991). ERD/ERS can be studied as a function of time, frequency and space. The ERD/ERS features have been employed extensively and successfully for BCI applications (McFarland et al., 2000; Neuper et al., 2003; Neuper et al., 2005; Pfurtscheller et al., 2006).

In this Ph.D. project, both MRCP features and ERD/ERS features were extracted from single trial and organized into a feature vector for classification.

1.4 State of the art of BCI

BCI differ in the brain signals used, the degree of freedom, how the subjects are trained and how the brain signals are translated into the device commands. In the following, a brief introduction on the most common, currently available BCIs is provided. Then signal processing and pattern recognition tools for BCI applications are introduced.

Present day BCIs

Slow Cortical Potential (SCP) BCI: SCP shifts up to several seconds in low frequency band, as shown in Fig. 8. The SCP-BCI trains users to regulate SCP amplitude by means of feedback. The negative potential shifts represent increased neuronal activity whereas positive shifts are associated with reduced activities and resting (Birbaumer et al., 1999). In a series of classic studies, Birbaumer and his colleagues have shown that people can learn to control SCPs and thereby control the environment (Birbaumer et al., 1999). It has been tested extensively in people with late-stage ALS and has proven able to supply basic communication capabilities (Birbaumer et al., 2008; Kübler et al., 2007; Kübler et al., 2005). However, the users of SCP-BCI need extensive training which is in several 1-2h sessions/week over weeks or months (Wolpaw et al., 2002).

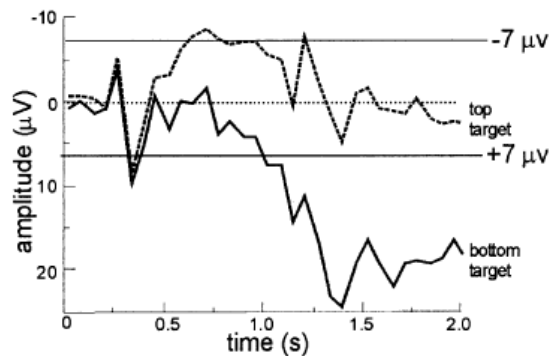


Figure 8. Slow cortical potentials (adapted from Wolpaw et al., 2002).

SensoriMotor Rhythm (SMR) BCI: The groups of Prof. Wolpaw in Albany, N.Y., and of Prof. Pfurtscheller in Graz, Austria, demonstrated in an extensive series of experiments that healthy subjects and paralyzed patients achieve voluntary control of right and left hemispheric SMR by imagining movements (Wolpaw et al., 1991; Pfurtscheller et al., 1997). By performing imaginary voluntary movements, such as right and left hand or foot movement, the user can control a cursor. Fig. 9 showed that two cursor movements (up and down) on a screen can be achieved by modulating mu rhythm (8-12 Hz). In this example, high amplitude of the mu rhythm corresponded to moving the cursor to the top target, while reduced amplitude to the bottom target (Wolpaw et al., 2002).

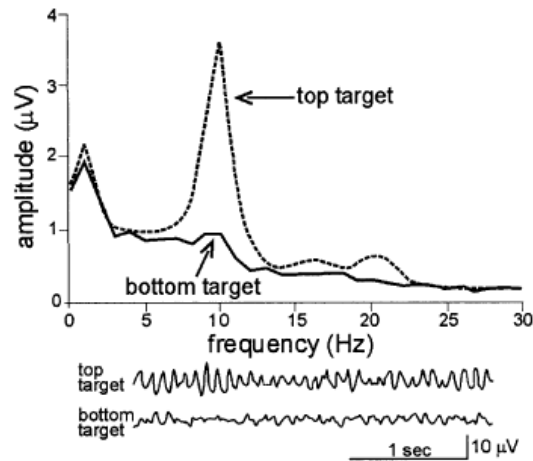


Figure 9. SensoriMotor rhythm (adapted from Wolpaw et al., 2002).

P300 BCI: The P300 component shown in Fig. 10 is a positive peak at approximately 300 ms after infrequent and surprising presentation of target stimuli (Sutton et al., 1965; Donchin and Smith, 1970). Farewell and Donchin have shown that P300 can be used to select items on a computer screen (Farwell and Donchin, 1988). The advantage of P300-BCI is that learning of self regulation of brain response and feedback is not necessary and the short latency of the P300 (300 ms instead of seconds in SCP and SMR based BCI) allows faster selection of letters. However, P300-BCIs rely on the user's ability to internally spell at high speed, an intact visual system, and intact attention (Birbaumer and Cohen, 2007). These requirements limit the use of P300-BCIs.

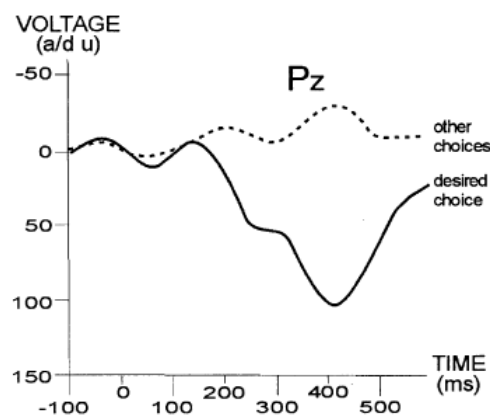


Figure 10. P300 evoked potential (adapted from Wolpaw et al., 2002).

The Steady State Evoked Potential (SSVEP)-BCI: SSVEP shown in Fig. 11 is elicited by external visual stimuli, which is flickering target under specified frequency. When participants focused their gaze on the flickering target, the amplitude of SSVEP increased at the fundamental frequency of the target and their harmonics (Müller-Putz et al., 2006; Nielsen et al., 2006; Wang et al., 2006). It can be recorded from the visual cortex located in the occipital lobe and detected easily in frequency domain. Like P300-BCI, SSVEP-BCI requires attention and intact gaze control. The advantage with SSVEP BCI is no extensive training involved and multi-degree of freedom.

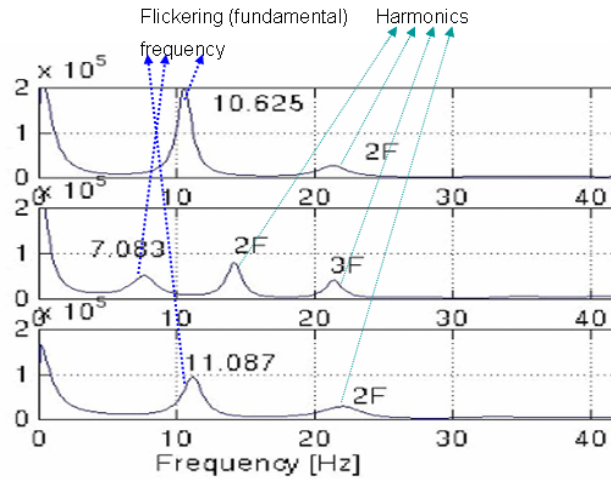


Figure 11. Steady state evoked potential (adapted from Gu master thesis)

Signal processing and pattern recognition for BCI application

BCI research involves the development of techniques which translate high dimensional EEG signals produced by the brain into a control command. The biofeedback approach (Birbaumer et al., 1999) instructed subjects to learn to voluntarily control brain activity by means of a feedback signal generated by a fixed translation algorithm. In such a system, the users' learning is important and requires extensive training. In contrast, machine learning approaches detect the characteristics of the brain signals resulting from specific events. Machine learning plays an important role in dealing with variability among subjects and within the same subject over time. Current BCIs use machine learning in two distinct phases: feature extraction and classification. Prominent techniques for feature extraction and classification are presented in the following sections.

Feature extraction: Starting with raw EEG signals, one has to extract relevant information which can lead to good classification performance. This procedure decreases the dimensionality of the raw EEG signal. Spectral filtering and spatial filtering are commonly used to extract relevant characteristics of EEG signals. Spectral filtering aims to get signals at desired frequency bands according to a prior neurophysiology knowledge. It is commonly done by finite and infinite impulse response filters or joint time-frequency analysis methods (wavelet, short-time Fourier transformation (STFT), and so on) (Pfurtscheller and Lopes da Silva, 1999). Raw EEG signals are associated with a large spatial scale due to volume conduction. Spatial filtering techniques are used to get more localized signals. Commonly used techniques are bipolar filtering (Wang and He, 2004), Laplace filtering (Pfurtscheller et al., 2006; Wang and He, 2004), principle component analysis (PCA) (Fatourehchi et al., 2004), independent component analysis (ICA) (Qin et al., 2004), common spatial patterns (CSP) (Guger et al., 2000).

Classification: Given empirical data points (x_i, y_i) for $i=1, \dots, n$ with $x_i \in R^m$ in the Euclidean space and $y_i \in \{1, \dots, N\}$ as class labels for $N > 2$ different classes or $y_i \in \{\pm 1\}$ as class labels for a binary problem, the goal of the classification is to find a generalization function f that predicts the label of future unseen data points x . The

current classification methods used for BCI include quadratic discriminant analysis (QDA) (Neuper et al., 1999), linear discriminant analysis (LDA) (Donoghue et al., 2004), regression (Wolpaw and McFarland, 2004; McFarland and Wolpaw, 2005), fisher discriminant analysis (Mika et al., 2001), support vector machine (SVM) (Müller et al., 2001; Farina et al., 2007), linear programming machine (Bennett and Mangasarian, 1992), kernel methods (Müller et al., 2001), and so on.

The most objective report of BCI accuracy is feedback results. But, when working with online system and pursuing feedback experiments, one has to validate and tune the classification algorithm first. The evaluation of algorithm performance and tuning parameters of the algorithm can be achieved by a nested cross-validation. In general, the data samples are split in many different ways into training set and test set. The inner cross-validation performed on the training set aims to do the generalization; the outer cross-validation aims to get an estimation of the generalization error (Müller et al., 2001; Birch & Mason, 2000; Fatourechi et al., 2008).

1.5 Clinical application of BCI

Many diseases such as traumatic injury, stroke, or amyotrophic lateral sclerosis (ALS) may lead to motor paralysis. The locked in state (LIS) is the state in which only residual voluntary muscle control is possible, such as eye or lip movements. However, with progression of the disease, the patients may enter into the complete locked in state (CLIS) in which all voluntary movements are lost. In both states, the patients' sensory, emotional and cognitive processing remains largely intact (Kübler et al., 2007). In particular, ALS progresses on average over a period of three years from the first symptoms of muscular weakness to respiratory failure. Artificial feeding and ventilation are thus necessary at the later stages. BCIs provide a promising solution to the severely disabled individuals for interacting with the environment.

BCI attraction for people with less impairing disabilities depends on the speed and precision of the control, the degree of freedom and the applications that BCI can provide. The effective brain signals to BCI may vary among people with different disabilities, due to the particular underlying central nervous system (CNS) abnormality. The specific BCI methods and applications should be assessed by the individual needs and convenience and complexity of the system.

Three types of EEG based BCI systems have been tested on patients: SCP-BCI, SMR-BCI and P300-BCI. After extensive training, severely disabled and LIS patients have communicated messages of considerable length by self regulation of SCP (Neumann et al., 2003; Kübler et al., 2007). It has been reported that by control of SMR amplitude, LIS patients can spell using a so-called virtual keyboard (Obermaier et al., 2003). The spelling rate varied in the range 0.2-2.5 letters/minute (Neuper et al., 2003). When confronted with P300-BCI, ALS patients were able to achieve accuracies up to 100% (Sellers et al., 2006). Moreover, ALS patients can use P300-BCI systems with online accuracies of up to 79%, with stable performance over several months (Nijboer et al., 2008). SCP-BCI require many training sessions over weeks or months on learning self regulation of brain activities. Training is not necessary for P300-BCI, but it relies on the selective attention and gaze control. Both LIS and CLIS patients show intact audition and tactile perception assessed by event

related potentials (ERPs) (Kotchoubey, 2005). Therefore, BCI must use auditory and tactile modality for CLIS patients (Birbaumer et al., 2008).

1.6 Overview of the Ph.D. project

The BCI paradigm developed in this Ph.D. is based on imagining voluntary movements with varied movement-related parameters on the same joint. The purpose was to distinguish between two tasks involving different combinations of movement parameters, as a continuation of preliminary works performed at Aalborg University (do Nascimento et al., 2005; Nielsen et al., 2006; Farina et al., 2007). The studies have been focusing on two topics: a) analyzing the effect of the movement parameters from the MRCP perspective and understanding which movement parameters were best for differentiation; b) 2-class classification in single trial. The developed classification algorithm based on distinguishing speeds of movements has been tested on ALS patients offline. It achieved on average 70% classification accuracy with approximately 30 minutes of training. The obvious advantage of decoding movement parameters is that there is no extensive learning and training procedure involved compared with SCP-BCI. In contrast with SMR-BCI based on distinguishing different limbs' movement to increase degree of freedom, this study proposes an alternative and extendable strategy to increase the degrees of freedom. Compared with P300-BCI, this new BCI paradigm does not require visual selective attention or gaze control. Therefore, it can benefit more locked-in users. Testing on more target users and testing online should be performed to provide strong evidence for advantages of the BCI paradigm developed in this project. The following paragraphs describe pattern recognition implemented and aim of the project.

1.6.1 Pattern recognition implemented in this Ph.D. Project

The applied pattern recognition method is derived from that described by Farina et al. (2007) and is based on features extracted with wavelet transform and on classification performed with Support Vector Machine (SVM). Fig. 12 shows the structure of the algorithm.

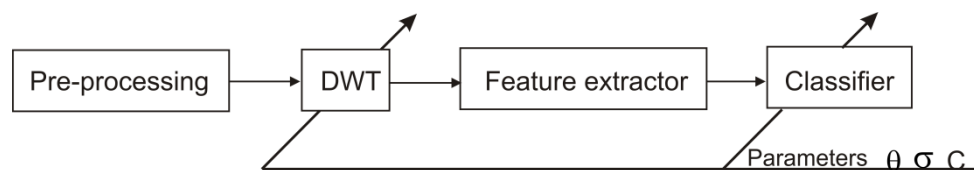


Figure 12. Block diagram of the algorithm used for single-trial classification. θ is the parameter for tuning the mother wavelet. σ and C are the parameters of the SVM classifier.

Features

The discrete wavelet transform (DWT) decompose the signal into different scales with multiple resolutions by dilating a mother wavelet. The selection of the mother wavelet provides the way for obtaining a feature space adapted to a specific classification problem. The parameterization of the mother wavelet can be realized by the Multi Resolution Analysis (MRA) (Burrus et al., 1997) framework, in which the scaling

function ϕ and its associated wavelet function ψ are related to the Finite Impulse Response (FIR) filters h and g by the two-scale relations (Mallat 1989):

$$\phi(t/2) = \sqrt{2} \sum_n h[n] \phi(t-n)$$

$$\psi(t/2) = \sqrt{2} \sum_n g[n] \psi(t-n)$$

In order to generate an orthogonal wavelet using MRA, h must satisfy some conditions. For FIR filter of length L , there are $L/2-1$ sufficient conditions to ensure the existence and orthogonality of the scaling function and wavelets. If $L = 4$, one parameter θ , varying over the range $[-\pi, \pi]$, defines the decomposition (Maitrot et al., 2005; Farina et al., 2007). In this study, values of the parameter θ , uniformly distributed between $-\pi$ and π , were used to design h with length 4, therefore, a group of mother wavelet were used for optimization.

The DWT provides a set of detail coefficients $d_i(j, k)$, where 2^j is the scaling factor, k the translation parameter, and i the index identifying the mother wavelet. The marginals of the detail coefficients were the features used as inputs to the classifier:

$$m_i(j) = \sum_{k=0}^{N/2^j-1} |d_i(j, k)| \quad j=1, \dots, J; \quad M_i = [m_i(1), \dots, m_i(J)]$$

where J is the deepest level of the decomposition and N the length of the signal. The feature vector M_i contains information on the distribution of the wavelet coefficients over J bands. The analyzing wavelet was chosen on the basis of a learning step (supervised classification), as described below. The MRCP energy is mainly concentrated at low frequencies (approximately up to 1 Hz), whereas the mu rhythm (8-12 Hz) and beta rhythm (18-25 Hz) are at higher frequencies. Frequency bands in feature vector are either selected manually covering the low frequency band for MRCP and SMR or full frequency bands are selected for feature vector.

Support vector machines (SVMs)

A non-linear SVM classifier with Gaussian kernel of parameterized width was used in this study. The central idea is to classify data from two classes by building a hyperplane from a training set. Given a training set (x_i, y_i) , $i=1, \dots, N$ where $x_i \in R^n$ and $y_i = \{\pm 1\}$, the standard SVM requires the solution of the following optimization problem (Bishop, 1995):

$$\min_{w, b, \xi} \frac{1}{2} w^T w + c \sum_{i=1}^N \xi_i$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0.$$

where the function ϕ map x_i into a higher dimensional space. w is the weight vector and b is the bias of the hyperplane. A slack variable (ξ_i) and a penalty parameter (c) are introduced if the training data cannot be separated without error. As a consequence, training samples can be at a small distance ξ_i on the wrong side of the hyperplane. In practice, there is a trade-off between a low training error and a large margin. This trade-off is controlled by the penalty parameter c . The following steps were carried out for classification with SVM.

Scaling: data were linearly scaled. The class A is represented by the matrix $A_{J \times N_1}$ (J frequency bands, N_1 number of trials from class A) and the class B by $B_{J \times N_2}$ (N_2 number of trials from class B). They represent two imagination tasks, respectively.

$$a = \max(A_{J \times N_1}) \quad b = \max(B_{J \times N_2}) \quad s = \max(a, b)$$

$$\text{Then } A_{\text{scaled}} = A_{J \times N_1} / s, \quad B_{\text{scaled}} = B_{J \times N_2} / s$$

Kernel selection: the Gaussian kernel $K(x, y) = \exp(-\frac{\|x - y\|^2}{2\sigma^2})$ was chosen. This kernel depends only on one parameter σ .

Cross-validation: a double 3-fold cross-validation was applied to test the results. The signal data set was randomly divided into 3 subsets of equal size. One subset was used as testing set and the remaining 2 subsets as training set (first cross-validation). The signals in the training set were further divided into 3 subsets of equal size (second cross-validation), two used for optimizing the parameters and the last for estimating the probability of error of the optimized parameters (this cross-validation was performed for generalization purposes). The set of parameters were searched by the inner cross-validation in the ranges chosen empirically. The set of parameters (c , σ , θ) corresponding to the lowest probability of error estimated from the inner cross-validation was applied to the test set.

1.6.2 Aim and structure of the Ph.D. project

The aim of the Ph.D. project is to contribute to developing a natural BCI system for complex motor controls for severely disabled individual. To achieve the goal, we investigated the possibility of distinguishing movement parameters on a single trial basis by imagining movements of the same joint performed at different speeds and force levels. Extensive previous work has been devoted to distinguishing movements from different joints with the purpose of increasing the number of degrees of freedom. The approach proposed in this Ph.D. project, based on classifying movement parameters from the same joint, could further increase the degrees of freedom of BCIs and make BCI control more natural.

One of the outcomes of this project is that the speed of an imagined movement was encoded in the rebound rate of MRCPs and can be better discriminated than other movement parameters in healthy volunteers. The developed pattern recognition was

further applied to ALS patients. In these patients, the time delay of peak negativity was influenced by the speed of the imagined movement. The use of speed as the variable to discriminate has advantages with respect to other strategies, as it was observed in the clinical study. It was easy to instruct patients about it either by showing them another person doing the movement or by holding the patients' joint to perform the movement passively. The difference between fast and slow speed was quite obvious and intuitive. The tasks themselves were well predefined. The patients knew the tasks to be performed exactly in the beginning. Therefore it saved training time, making BCI use more convenient and less frustrating.

The Ph.D. project was organized into three studies as shown in Fig. 13. Study 1 and Study 2 were basic studies on healthy volunteers involving the methodological developments and implementations of the pattern recognition methods. Study 3 was a clinical study on ALS patients performed at the Institute of Medical Psychology and Behavioral Neurobiology, Eberhard-Karls-University, Tuebingen, Germany. Study 3 was based on the methods developed and the results obtained in Studies 1 and 2.

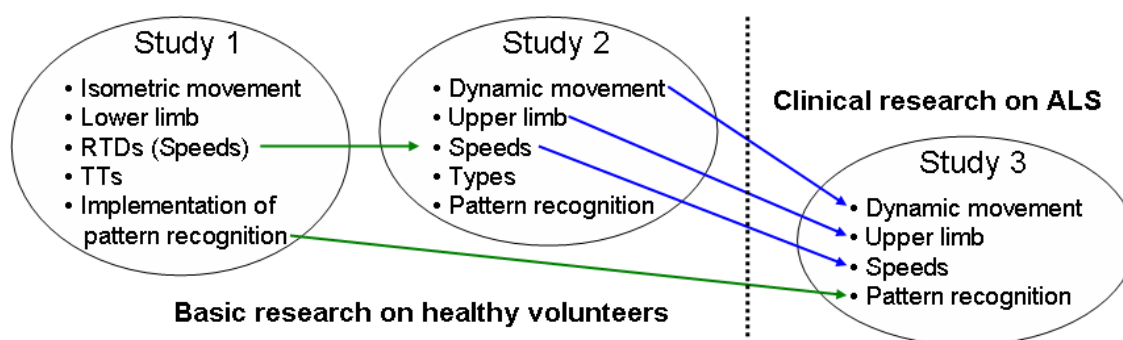


Figure 13. Structure of Ph.D. project (RTD: Rate of Torque Development; TT: Target Torque; ALS: Amyotrophic Lateral Sclerosis).

Study 1

Study 1 was performed on nine healthy subjects aged 22-33 years (three women and six men). None had known sensory-motor deficits or any history of psychological disorders. Study 1 aimed to investigate the accuracy in discriminating combinations of rate of torque development (RTD) and target torque (TT) and assess if any combination of these two parameters would be preferable. It was based on imagining isometric plantar flexion (lower limb) in four conditions involving two RTDs and two TTs (see Article I). The outcomes of the two-class classifications showed that RTD (speed) can be better classified than TT. It also showed that the selection of movement parameters' combination and scalp location which led to the best performance varied largely among subjects.

Study 2

Study 2 was carried out on nine healthy subjects aged 22-30 years (four women and five men). None had known sensory-motor deficits or any history of psychological disorders. The subjects who participated in this study were different from those of Study 1. Based on the results of Study 1, in Study 2 we aimed to develop a more practical BCI system for severely disabled people in terms of easy instruction on

imagery tasks and less training time. A dynamic task can be more easily explained and is more intuitive than an isometric task. Moreover, the cortical representation area for hand/wrist is larger than that for the foot. Thus, we moved to investigate imagining dynamic movements rather than isometric movements, and to analyze wrist movements (upper limb) rather than plantar movements (lower limb). Based on the result of Study 1 that speed was better differentiated than TT, two speeds were examined in Study 2. In addition, two wrist movements (wrist extension and wrist rotation) were also investigated. Thus, the volunteers performed wrist extension and rotation at two speeds (see Article II). The results showed that speed can be better distinguished than movement type at the same joint.

Study 3

Study 3 was carried out on four ALS patients aged 40-70 years (three women and one man) (Article III). The techniques developed from the previous two studies were tested on patients. Based on the results from Study 1 and Study 2, the ALS patients were asked to imagine wrist extension at two speeds. The instruction on imagery tasks and experimental procedure lasted approximately 30 minutes. The same pattern recognition method as described in Study 1 was applied. The classification error ranged from 25% to 34% for patients. Binomial test performed for each subject showed that single trial classification accuracies were above chance level for all patients ($p < 0.004$). The average classification error (30%) is acceptable for this clinical application due to the following reasons. First, the recording was performed at the patients' home place where there were strong electromagnetic interferences and other environmental noise. Therefore the quality of the EEG signals was worse compared with recordings performed in the laboratory. Second, the classification of movement parameter from one joint is much more difficult than that of movements from different limbs. Third, there was no training and feedback involved for patients. It is expected that with training over several sessions and feedback, the classification accuracy will be improved. This result indicated that the developed methods can be potentially used by severely disabled patients.

The number of subjects in Study 3 was small due to the difficulty in finding patients for these types of experiments. Each patient showed characteristic changes during imagination tasks and the classification accuracy was above chance significantly after individual temporal-spatial optimization. However, more tests need to be done on ALS patients to provide stronger evidence on the reliability and usability of proposed new BCI paradigm.

1.7. Conclusions and future perspectives

The development of BCI research for communication and control has been driven by its wide application potentials. Clinical applications of BCI in rehabilitation are becoming evident. BCI is a promising solution for patients suffering from locked-in syndrome or other severe paralysis to interact with the environment. In addition to clinical and quality of life issues, such interfaces have served as powerful tools for improving understanding of fundamental functions of brain.

According to the individual needs or different underlying abnormality of the central nervous system (CNS) of the target users, the BCI systems should be adapted in terms

of selection of scalp location, EEG features, time window, and so on. The pattern recognition method implemented in this Ph.D. project overcomes the large inter-subject variability by tuning the parameters related to feature extraction and classification for each individual. The studies conducted during this Ph.D. project have focused on investigating the effect of movement-related parameters on MRCPs from the same joint. The relevant MRCP and well studied ERD/ERS features were extracted for classification. The average misclassification rate of 20% and 30% for healthy volunteers and ALS patients, respectively, have indicated that movement-related parameters could serve as an alternative or supplementary input signal for BCI.

There are quite some future studies that may be suggested from this thesis. The effect of movement speed on ERD/ERS should be analyzed to better understand the brain functions. In this project, slow movements took approximately 3 s. A larger range of movement times could be considered in the future. In this way, the speed of BCI systems could be potentially increased. Online classification of speed should be implemented to examine if online feedback and training can improve the accuracy of the proposed system. The multi-classes (for example left and right wrist extension at two speeds) classification should be evaluated. Decoding of movement parameters should be tested online in patients.

The EEG-based BCIs have begun to provide basic communication and motor control abilities to people with severe disabilities. Their future potential and importance depend on the functions they can provide, and the safety, speed, convenience and reliability of long time use. This Ph.D. project has contributed to the BCI system in terms of improving the convenience of use of BCI and increasing the degree of freedom. The project has proposed, designed, and validated offline a new BCI paradigm on both healthy volunteers and ALS patients.

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